Informational efficiency of loans versus bonds: Evidence from secondary market prices

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Abstract

This paper examines the informational efficiency of loans relative to bonds surrounding loan default dates and bond default dates. We examine this issue using a unique dataset of daily secondary market prices of loans over the 11/1999-06/2002 period. We find evidence consistent with a monitoring role of loans. Specifically, consistent with a view that the monitoring role of loans should be reflected in more precise expectations embedded in loan prices, we find that the price decline of loans is less adverse than that of bonds of the same borrower around loan and bond default dates. Additionally, we find evidence that the difference in price decline of loans versus bonds is amplified around loan default dates that are not preceded by a bond default date of the same company. Our results are robust to several alternative explanations, and to controlling for security-specific characteristics, such as seniority, collateral, covenants, and for multiple measures of cumulative abnormal returns. Overall, we find that the loan market is informationally more efficient than the bond market around loan default dates and bond default dates.

JEL Classification Codes: G14, G21, G22, G23, G24

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1. Introduction

The monitoring role of bank lending has been well documented in the literature. Several theoretical models highlight the unique monitoring function of banks (e.g., Diamond, 1984; Ramakrishnan and Thakor, 1984; Fama, 1985). These studies generally argue that banks have a comparative cost advantage in monitoring loan agreements. For example, Diamond (1984) contends that banks have scale economies and comparative cost advantages in information production that enable them to undertake superior debt-related monitoring. Ramakrishnan and Thakor (1984) show that banks as information brokers can improve welfare by minimizing the costs of information production and moral hazard. Fama (1985) argues that banks, as insiders, have superior information due to their access to inside information whereas outside (public) debt holders must rely mostly on publicly available information. Several empirical studies also provide evidence on the uniqueness of bank loans, e.g., James (1987), Lummer and McConnell (1989), and Billett, Flannery and Garfinkel (1995).[1]

It may be noted that the incentives to monitor are likely to be preserved even in the presence of loan sales in the secondary market.[2] First, the lead bank, which typically holds the largest share of a syndicated loan (see Kroszner and Strahan (2001)) rarely sells its share of a loan. Conversations with industry experts suggest that there are at least two reasons for this: (a) to preserve its banking relationship with the borrower, and (b) the lead bank is also typically the administrative agent, and has a fiduciary responsibility to the rest of the banks and investors to provide timely information on the borrower. Second, not all participants in a loan syndicate sell their share of a loan, and therefore continue to have incentives to

[1] These studies examine the issue of whether bank lenders provide valuable information about borrowers. For example, James (1987) documents that the announcement of a bank credit agreement conveys positive news to the stock market about the borrowing firm's credit worthiness. Extending James' work, Lummer and McConnell (1989), show that only firms renewing a bank credit agreement have a significantly positive announcement period stock excess return. Billet, Flannery, and Garfinkel (1995) show that the impact of loan announcements is positively related to the quality of the lender.

[2] Possible reasons for loan sales include a bank's desire to mitigate "regulatory taxes" such as capital requirements (see, e.g., Pennacchi (1988)), to reduce the underinvestment problem of loans (see, e.g., James (1988)), and to enhance origination and distribution abilities of banks (practitioners' viewpoint). The only study that empirically examines the impact of a loan sale on the borrower and on the selling bank is Dahiya, Puri, and Saunders (2003), who find, on average, that while the stock returns of borrowers are significantly negatively impacted, the stock returns of the selling banks are not significantly impacted surrounding the announcement of a loan sale.

monitor. For example, commercial banks in a syndicate are typically known to adopt a buy and hold (till maturity) strategy. Finally, the changing role of banks, from loan originators to loan dealers and traders, which facilitated the development of a secondary market for loans (See Taylor and Yang (2003)), may provide additional channels of monitoring. For example, a bank who serves as a loan dealer will have incentives to monitor loans that are in its inventory. Consequently, the monitoring role of loans has important implications for the informational efficiency of the loan market versus the bond market. That is, as skilled loan monitors with incentives to monitor, so called delegated monitors, banks collect information on a frequent basis, and should be able to reflect such information in the secondary market loan prices in a timely manner. Hence, the surprise or unexpected component of an event, such as a default is likely to be smaller for banks than for bond investors because banks are continuous monitors as compared to investors in the bond markets where monitoring tends to be more diffuse and subject to free rider problems.[3]

The informational efficiency of the bond market relative to the stock market has received increasing attention. For example, using a dataset based on daily and hourly transactions for 55 high-yield bonds on the National Association of Securities Dealers (NASD) electronic fixed income pricing system (FIPS) between January 3, 1995 and October 1, 1995, Hotchkiss and Ronen (2002) find that the informational efficiency of corporate bond prices is similar to that of the underlying stocks. Specifically, they document that the information in earnings news is quickly incorporated into both bond and stock prices, even on an intraday level.

[3]We view that loan investors, such as banks, have the skills and the incentives to act as continuous monitors as compared to investors in the bond markets where monitoring tends to be more diffuse and subject to free rider problems. Data from the Dealscan database of the Loan Pricing Corporation (LPC) shows that a loan syndicate averaged 6.3 lenders per deal during 2002, and the average deal size was $356 million. The comparable numbers for bond issue syndicates from the Global New Issues database of the Securities Data Company (SDC) during the same period were 5.22 lenders per bond syndicate, and the average bond issue was $251 million. Assuming a linear relationship between the average issue size and the size of the syndicate, one would expect 7.4 lenders for an equivalent bond issue of average size of $356 million (i.e., 5.22*356/251) – the size of the loan syndicate at 6.3 lenders is slightly lower than the expected 7.4 lenders. More importantly, based on reasons described earlier (e.g., preserving a banking relationship), a lender in a loan syndicate is more likely to hold its share of a loan than distribute it as compared to a lender in a bond syndicate, which suggests that the number of investors that typically hold a bond issue at any particular point in time is likely to be larger than that of a loan issue, resulting in diffused monitoring by the bond investors due to free-rider problems. Conversations with industry experts also confirm our understanding of the monitoring incentives in the loan market as compared to the bond market.

Other studies have found a strong contemporaneous relationship between corporate bond returns and stock returns.[4]

There is also a growing literature that indirectly contributes to the informational efficiency debate by examining institutional bond trading costs. Using a large dataset of corporate bond trades of institutional investors from 1995 to 1997, Schultz (2001) documents that the average round-trip trading costs of investment grade bonds is \$0.27 per \$100 of par value. Schultz also finds that large trades cost less, large dealers charge less than small dealers, and active institutions pay less than inactive institutions. Interestingly, Schultz finds that bond ratings have little effect on trading costs.[5]

However, there is no study to date that examines the informational efficiency of the secondary market for loans relative to the market for bonds of the same corporation, largely due to unavailability (at least until now) of secondary market prices of loans. The market for loans includes two broad categories, the first is the primary or syndicated loan market, in which portions of a loan are placed with a number of banks, often in conjunction with, and as part of, the loan origination process (usually referred to as the sale of participations). The second category is the seasoned or secondary loan sales market in which a bank subsequently sells an existing loan (or part of a loan). In addition, the secondary loan sales market is sometimes segmented based on the type of investors involved on the "buy-side", e.g., institutional loan market versus retail loan market. A final way of stratifying loan trades in the secondary market is to distinguish between the "par" loans (loans selling at 90% or more of face value) versus "distressed" loans (loans selling at below 90% of face value). Figure 1 shows the rate of growth in the secondary market for loans, stratified by this last categorization from 1991-2002. Note the growth in the market up to 2000 when the level of secondary loan transactions topped \$100 billion for the first time. Note also the increasing proportion of distressed loan sales reached 42% in 2002.

Our study focuses on the informational efficiency of the loan market relative to the bond

[4] See, for example, Blume et al (1991), and Kwan (1996) for details.

[5] In a related study, Hong and Warga (2000) employ a sample of 1,973 buy and sell trades for the same bond on the same day and estimate an effective spread of \$0.13 for investment-grade bonds and \$0.19 for non-investment grade bonds per \$100 par value.

market around default dates, using a unique dataset of secondary market daily prices of loans. Our sample period covers more than two years, namely November 1, 1999 through June 30, 2002, a time of increasing level of corporate defaults.[6]

We hypothesize and test the following implication of a monitoring role of loans: Since loans are likely to have timely and superior expectations built into their prices relative to bonds because banks have the incentives and skills to act as continuous monitors as compared to investors in the bond markets where monitoring tends to be more diffuse and subject to free rider problems (see footnote 3 for details), this implies the unexpected (or surprise) component of a default event is likely to be lower for loans than for bonds. Consequently, one would expect the price reactions of loans to be significantly lower than that of bonds around both loan and bond default dates, controlling for different attributes, such as, maturity, size, seniority, collateral, and covenants of both instruments.[7]

Specifically, we pursue the following objectives: First, we examine return correlations of loans and bonds around loan and bond default dates as a first step to understanding whether loans have a monitoring advantage over bonds. Second, we empirically test the above mentioned hypothesis on the return performance of loans versus bonds around loan and bond default dates. To the best of our knowledge, ours is the first study to examine these issues using secondary market loan price data.

In addition to contributing to the literature on informational efficiency of financial markets, our study also contributes to the empirical literature on the monitoring role of loans. In this paper, we present a direct test of the monitoring hypothesis. This is in contrast to previous studies that tested the monitoring role of loans indirectly by examining the stock price reaction (rather than the loan price reaction) of a borrower to the announcement of a

[6]According to Standard & Poors, corporate defaults set a record in 2002, for the fourth consecutive year. The 234 companies and $178 billion of debt that defaulted during 2002 was the largest number and amount ever, exceeding the previous records of 220 companies and $119 billion in 2001. In 2000 there were 132 companies and $44 billion as compared to 107 companies and $40 billion in 1999. See Brady, Vazza and Bos (2003) for a historical summary of corporate defaults since 1980.

[7]The relevance of collateral in debt financing has been well-established in the literature. For example, Berger and Udell (1990) document that collateral plays an important role in more than two-thirds of commercial and industrial loans in the United States. John, Lynch, and Puri (2003) study how collateral affects bond yields.

new loan or the renewal of an existing loan to a borrower since they did not have access to secondary market loan price data.

Our main findings can be summarized as follows: First, while a small positive correlation exists between daily bond returns and loan returns, it is considerably higher during a 21 day event window [-10,+10], day 0 being the default date, as compared to other times in our sample. This finding is consistent with an increased importance of default risk premiums in explaining loan and bond returns, as compared to other factors[8], as we approach a default date. Second, consistent with a view that the monitoring role of loans should reflect in more precise expectations embedded in loan prices, e.g., the surprise or unexpected component of a default is likely to be smaller for loan investors than for bond investors, we find that the price reaction of loans is less adverse than that of bonds around loan and bond default dates. Third, where a loan default date is not preceded by a bond default date of the same company, we find that the differential in the price reaction of loans versus bonds is higher around such a loan default date. Our results are robust to several alternative explanations (e.g., recovery rates, and liquidity differences), to controlling for security-specific characteristics, such as maturity, size, seniority, collateral, covenants, and for multiple measures of cumulative abnormal returns around default dates. Overall, we find that the loan market is informationally more efficient than the bond market around default dates. Finally, preliminary evidence suggests that our results also extend to stocks, allowing us to make a similar assessment of the return performance of loans versus stocks.

The results of our paper have important implications in terms of the impact of defaults on loans and bonds, the monitoring of loans versus bonds, the benefits of loan monitoring for other financial markets (such as the bond market and the stock market), and on the benefits of including loans as an asset class in an investment portfolio along with bonds and stocks.

The remainder of the paper is organized as follows. Section 2 describes the data and sample selection. Section 3 presents the test hypothesis. Section 4 summarizes our empirical

[8]See Elton et al (2001) for an analysis of the determinants of corporate bond spreads (relative to Treasuries) who find that in addition to the expected default loss, other factors, such as taxes and risk premiums associated with Fama-French factors are important in determining corporate bond spreads.

results and Section 5 concludes.

2. Data and sample selection

The sample period for our study is November 1, 1999 through June 30, 2002. Our choice of the sample period was driven by data considerations, i.e., our empirical analysis requires secondary market daily prices of loans, which was not available prior to November 1, 1999.

We use several different data sources in this study. First, our loan price dataset is from the Loan Syndications and Trading Association (LSTA) and Loan Pricing Corporation (LPC) mark-to-market pricing service, supplied to over 100 institutions managing over $200 billion in bank loan assets.[9] This unique dataset consists of daily bid and ask price quotes aggregated across dealers. Each loan has a minimum of at least two dealer quotes and a maximum of over 30 dealers, including all top loan broker-dealers.[10] These price quotes are obtained on a daily basis by LSTA in the late afternoon from the dealers and the price quotes reflect the market events for the day. The items in this database include a unique loan identification number (LIN), name of the issuer (Company), type of loan, e.g., term loan (facility), date of pricing (Pricing Date), average of bid quotes (Avg Bid), number of bid quotes (Bid Quotes), average of second and third highest bid quote (High Bid Avg), average of ask quotes (Avg Ask), number of ask quotes (Ask Quotes), average of second and third lowest ask quotes (Low Ask Avg), and a type of classification based on the number of quotes received, e.g., Class II if 3 or more bid quotes. We have 543,526 loan-day observations spanning 1,863 loans in our loan price dataset.

Second, the primary source for our bond price dataset is the *Salomon* (now Citigroup) Yield Book. We extracted daily prices for all the companies for which we have loans in the loan price dataset. We have 371,797 bond-day observations spanning 816 bonds. Third, for

[9]Since LSTA and LPC do not make a market in bank loans and are not directly or indirectly involved the buying or selling of bank loans, the LSTA/LPC mark-to-market pricing service is expected to be independent and objective.

[10]At the time we received the dataset from LSTA, there were 33 loan dealers providing quotes to the LSTA/LPC mark-to-market pricing service.

robustness, we also created another bond price dataset from Datastream for a subset of loans with a bond default date or a loan default date (the primary focus of our study), containing 91,760 bond-day observations spanning 248 bonds.

Fourth, our loan default dataset consists of loan defaults from the institutional loan market. We received these data from Portfolio Management Data (PMD), a business unit of Standard & Poors which has been tracking loan defaults in the institutional loan market since 1995.[11]

Fifth, the source for our bond defaults dataset is the "New York University (NYU) Salomon Center's Altman Bond Default Database". It is a comprehensive dataset of domestic corporate bond default dates starting from 1974.

Sixth, the sources for the loan, bond and stock index returns are the S&P/LSTA Leveraged Loan Index from the Standard & Poor's, the Lehman Brothers U.S. Corporate Intermediate Bond Index from the Datastream, and the NYSE/AMEX/NASDAQ Value-weighted Index from the Center for Research in Securities Prices (CRSP).

Finally, security-specific characteristics, such as seniority, collateral and covenants were obtained from the Loan Pricing Corporation (LPC) for loans, the NYU Salomon Center's Altman Bond Default Database, and the Fixed Income Securities Database for bonds.

Due to an absence of a unique identifier that ties all these datasets together, time and care was spent in manually matching these datasets based on name of the company and other identifying variables, e.g., date (See Appendix 1 for more details on how these datasets were processed and combined).

3. Test hypothesis

In this section, we develop a test hypothesis pertaining to the informational efficiency of the loan market as compared to that of the bond market surrounding loan default dates and bond default dates. Our central premise is that loans have a monitoring advantage

[11] Portfolio Management Data, a unit of Standard & Poor's has recently changed its name to "Standard & Poor's Leveraged Commentary & Data".

over bonds. Several theoretical models highlight the unique monitoring function of banks (see, for example, Diamond, 1984; Ramakrishnan and Thakor, 1984; Fama, 1985). These studies generally argue that banks have a comparative cost advantage in monitoring loan agreements which helps reduce the moral hazard costs of new debt financing. For example, Diamond (1984) contends that banks have scale economies and comparative cost advantages in information production. Ramakrishnan and Thakor (1984) show that banks as information brokers can improve welfare by minimizing the costs of information production and moral hazard. Fama (1985) argues that banks, as insiders, have access to inside information whereas outside (public) debt holders must rely mostly on publicly available information, such as new bank loan agreements.[12] Further, diffused public debt ownership and the associated free-rider problem diminish bondholders incentive to engage in costly information production and monitoring. This results in higher agency costs relative to bank debt, which is typically concentrated. Several empirical studies also provide evidence on the uniqueness of bank loans (see, for example, James (1987), Lummer and McConnell (1989), and Billett, Flannery and Garfinkel (1995)). James (1987) documents that the announcement of a bank credit agreement conveys positive news to the stock market about the borrowing firm's credit worthiness. Extending James' work, Lummer and McConnell (1989), show that only firms renewing a bank credit agreement have a significantly positive announcement period stock excess return. Billet, Flannery, and Garfinkel (1995) show that the impact of loan announcements is positively related to the quality of the lender.

We argue that the incentives to monitor are likely to be preserved even in the presence of loan sales in the secondary market. First, the lead bank, which typically holds the largest share of a syndicated loan rarely sells its share of a loan to preserve its relationship with the borrower, and to fulfill the fiduciary responsibility (as the administrative agent) to provide timely information on the borrower to other syndicate banks and investors. Second, not all participants in a loan syndicate sell their share of a loan (e.g., commercial banks typically adopt a buy and hold strategy), and therefore continue to have incentives to monitor. Fi-

[12]James (1987) finds evidence that support an informational role that links loan agreements to favorable stock price reactions.

nally, the changing role of banks, from loan originators to loan dealers and traders, which facilitated the development of a secondary market for loans, may provide additional channels of monitoring (i.e., to monitor loans that are in its inventory). Consequently, the monitoring role of loans has important implications for the informational efficiency of the loan market versus the bond market. For example, loans are likely to have timely and superior expectations built into their prices because banks are continuous monitors as compared to investors in the bond market where monitoring tends to be more diffuse and subject to free rider problems. Hence, the unexpected (or surprise) component of a loan default or a bond default is likely to be lower for loans than for bonds.[13] This leads to the following hypothesis:

Default expectation hypothesis: The unexpected (or surprise) component of a default event is likely to be lower for loans relative to bonds.

Consistent with the default expectation hypothesis, we expect the price reaction of loans to be significantly lower than the price reaction of bonds around loan default dates and bond default dates, after controlling for contractual or security-specific attributes, such as, maturity, size, seniority and collateral, and covenants of both instruments.

4. Empirical results

We begin this section with an analysis of the return correlations of loans and bonds as the first step in understanding whether loans have a monitoring advantage over bonds. We follow this analysis with the results from testing the default expectation hypothesis.

4.1. Return correlations of loans and bonds

Table 1 presents the average return correlation, and average t-statistic of loan-bond pairs of the same company around loan and bond default dates. We compute a daily loan return based on the mid-price quote of a loan, namely the average of the bid and ask price of a

[13]This assumes a partial spillover of the loan monitoring benefits to bonds – if bonds realize the full benefit of loan monitoring, the information used in forming loan and bond prices is likely to be identical. Whether the spillover is full or only partial is finally an empirical issue. Our results, discussed in Section 4 are consistent only with a partial spillover of the benefit of loan monitoring from loans to bonds.

loan in the loan price dataset.[14] That is, a one day loan return is computed as today's mid-price divided by yesterday's mid-price of a loan minus one. The daily bond returns are computed based on the price of a bond in the Salomon Yield Book in an analogous manner. A correlation coefficient and a t-statistic (of whether a correlation coefficient is statistically different from zero) is computed for each loan-bond pair of the same company as long as we have at least five observations during the time period of interest.[15] While the return correlations are generally low − as we approach closer to a significant event, such as a default, a loan-bond pair shows a greater commonality or positive correlation in returns. For example, the average return correlation between loan-bond pairs of the same company is 0.43 (average t-statistic on the correlations is 2.64, significant at the 1% level) during the 21 day event window surrounding a loan default date as compared to 0.12 (average t-statistic 1.97, significant at the 5% level) during the 234 day estimation window preceding the 21 day event window. The corresponding loan-bond pair correlations around bond default dates are 0.15 during the 21 day event window as compared to 0.01 during the 234 day estimation window − however, the average t-statistics on the correlations are not statistically significant at any meaningful level of significance. This finding reflects the increasing importance of default risk premiums in explaining loan and bond returns as compared to other factors (see footnote 8) as we approach a default date.

For robustness purposes, we also used daily bond returns from the Datastream instead of the Salomon Yield Book. These correlations (not shown here) are similar to the ones in Table 1. Hence for the remainder of the paper, we present our results using bond return data from the Salomon Yield Book.

Correlations such as those presented in Table 1 provide useful information about the commonality of returns.[16] However, to understand the magnitude of the difference in return

[14]We calculate returns based on the mid-price, i.e., the quote mid point to abstract away from the bid-ask bounce. See, for example, Stoll (2000) and Hasbrouck (1988) for more details.

[15]We test whether a specific correlation coefficient is statistically different from zero by comparing $\frac{r_{xy}\sqrt{N-2}}{\sqrt{1-r_{xy}^2}}$, where r_{xy} is the correlation coefficient, N is the number of observations, with the critical value from a t-distribution with $N-2$ degrees of freedom at the desired level of significance based on a two-tailed test. See SAS Procedures Guide (Version 8) for more details.

[16]We find that the price correlations (not reported in Table 1) also exhibit a similar pattern of an increase

performance, one needs to examine the cumulative abnormal returns surrounding default dates. We turn our attention to these measures in the following subsections.

4.2. Return performance around default dates

In this section, we empirically test the default expectation hypothesis. First, we present univariate comparisons of cumulative abnormal returns of loan-bond pairs, matched based on the name of the borrower. Next, we follow our univariate analysis with evidence from multivariate tests where we simultaneously control for security specific characteristics, such as maturity, issue size, seniority, and collateral of loans and bonds.

4.2.1. Univariate results

We conduct an event study analysis to examine the impact of corporate defaults on secondary market loan prices and bond prices. We examine two types of default, namely loan defaults, and bond defaults. We measure return performance surrounding default dates by cumulating daily abnormal returns during a pre-specified window surrounding a default date. We present empirical evidence for three different event windows: 3-day window [-1,+1], 11-day window [-5,+5] and a 21-day window [-10,+10], where day 0 refers to the default date.

We use several different methods to compute daily abnormal returns. First, on an unadjusted basis, i.e., using the raw returns, as a first-approximation of the magnitude of the return impact on a loan or a bond of the same corporation around default dates. Three other return measures are also examined based on test methodologies described in Brown and Warner (1985). Specifically and secondly, a mean-adjusted return, i.e., average daily return during the 234 day estimation time period ([-244,-11]), is subtracted from a loan or bond daily return. The third and fourth measures are based on a single-factor market index

in magnitude during the 21 day event window surrounding a default date. For example, the average price correlation of a loan-bond pair of the same company is 0.82 (average t-statistic 11.30, significant at the 1% level) during the 21 day event window surrounding a loan default date as compared to 0.57 (average t-statistic 13.94, also significant at the 1% level) during the 234 day estimation window preceding the 21 day event window. The corresponding loan-bond pair correlations around bond default dates are 0.61 (average t-statistic 5.39, significant at the 1% level) during the 21 day event window as compared to 0.46 (average t-statistic 9.97, also significant at the 1% level) during the 234 day estimation window.

(we use the S&P/LSTA Leveraged Loan Index as a market index for loans, and the Lehman Brothers U.S. Corporate Intermediate Bond Index as a market index for bonds).[17] Thus, the third measure is a market-adjusted return, i.e., the return on a market index is subtracted from a loan or bond daily return and the fourth is a market-model adjusted return, i.e., the predicted return based on a market-model regression is subtracted from a loan or bond return. We also used two different types of multi-factor models for estimating abnormal returns: (a) a three-factor model where the three factors are the return on a loan index, the return on a bond index, and the return on a stock index, and (b) the three-factor model of Fama and French (1993).[18] The predicted return from a multi-factor model is subtracted from a loan or bond daily return. More formally,

$$A_{i,t} = R_{i,t} - E[R_{i,t}], \tag{1}$$

where $A_{i,t}$ is the abnormal return, $R_{i,t}$ is the observed arithmetic return,[19] and $E[R_{i,t}]$ is the expected return for security i at date t. The six different methods of computing daily abnormal returns correspond to six different expressions for the expected return for security i at date t. That is,

$$E[R_{i,t}] = \begin{cases} 0 & \text{unadjusted} \\ \bar{R}_i & \text{mean-adjusted} \\ R_{MKT,t} & \text{market-adjusted} \\ \hat{\alpha}_i + \hat{\beta}_i R_{MKT,t} & \text{market-model adjusted} \\ \hat{\alpha}_i + \hat{\beta}_{i,1} R_{L,t} + \hat{\beta}_{i,2} R_{B,t} + \hat{\beta}_{i,3} R_{S,t} & \text{three-factor model adjusted} \\ \hat{\alpha}_i + \hat{\beta}_{i,1} R_{S,t} + \hat{\beta}_{i,2} R_{HML,t} + \hat{\beta}_{i,3} R_{SMB,t} & \text{three-factor model (Fama-French) adjusted} \end{cases}$$

[17]While the Lehman Brothers U.S. Corporate Intermediate Bond Index is a daily series, the S&P/LSTA Leveraged Loan Index is a weekly series during our sample period. For computing market-adjusted and market-model adjusted daily abnormal returns of loans around default dates, we converted the S&P/LSTA Leveraged Loan Index weekly series to a daily series through linear intrapolation.

[18]The returns on the Fama and French (1993) factors are obtained from Professor Kenneth French's website http://mba.dartmouth.edu/pages/faculty/ken.french/.

[19]That is, $R_{i,t} = P_{i,t}/P_{i,t-1} - 1$, where $P_{i,t}$ and $P_{i,t-1}$ denote the price for security i at time t and t-1.

where $\bar{R}_i$ is the simple average of security i's daily returns during the 234-day estimation period (i.e., [-244,-11]):

$$\bar{R}_i = \frac{1}{234} \sum_{t=-244}^{t=-11} R_{i,t}. \tag{2}$$

$R_{MKT,t}$ is the return on a market index defined as below:

$$R_{MKT,t} = \begin{cases} R_{L,t} & \text{loan index} \\ R_{B,t} & \text{bond index} \\ R_{S,t} & \text{stock index} \end{cases}$$

where $R_{L,t}$ is the return on the S&P/LSTA Leveraged Loan Index, $R_{B,t}$ is the return on the Lehman Brothers U.S. Corporate Intermediate Bond Index, $R_{S,t}$ is the return on NYSE/AMEX/NASDAQ value-weighted index, $R_{HML,t}$ is the return on a zero-investment portfolio return based on book-to-market, and $R_{SMB,t}$ is the return on a zero-investment portfolio return based on size for day t. The coefficients $\hat{\alpha}_i$ and $\hat{\beta}_i$ are Ordinary Least Squares (OLS) values from the market-model regression during the estimation time period. That is, we regress security i's returns on market index returns and a constant term to obtain OLS estimates of $\hat{\alpha}_i$ and $\hat{\beta}_i$ during the estimation time period.[20] The intercept and slope coefficients for the multi-factor models are defined analogously to the single-factor models.

The test statistic under the null hypothesis (of zero abnormal returns) for any event day and for multi-day windows surrounding default dates is described below.[21] The test statistic for any day t is the ratio of the average abnormal return to its standard error, estimated from the time-series of average abnormal returns. More formally,

[20]Where we do not have return data for the full estimation period, to ensure that we have reasonable estimates (e.g., lower standard errors), we require at least 50 observations to compute the mean-adjusted and market-model adjusted abnormal returns. While the unadjusted and market-adjusted abnormal return procedures do not need any minimum number of observations, we still employ the same criteria of requiring at least 50 observations to ensure comparability of the different abnormal return measures.

[21]Please see Brown and Warner (1985), pp. 7-8, and pp. 28-29 for more details.

$$\frac{\bar{A}_t}{\hat{S}(\bar{A}_t)} \sim N(0,1), \tag{3}$$

where $\bar{A}_t$ and $\hat{S}(\bar{A}_t)$ are defined as

$$\bar{A}_t = \frac{1}{N_t}\sum_{i=1}^{N_t} A_{i,t}, \tag{4}$$

$$\hat{S}(\bar{A}_t) = \sqrt{\frac{1}{233}\left(\sum_{t=-244}^{t=-11}(\bar{A}_t - A^*)^2\right)}, \tag{5}$$

where A^* used in computing $\hat{S}(\bar{A}_t)$ is defined as

$$A^* = \frac{1}{234}\sum_{t=-244}^{t=-11}\bar{A}_t, \tag{6}$$

where N_t is the number of securities whose abnormal returns are available at day t. For tests over multi-day intervals, e.g., [-5,+5], the test statistic is the ratio of the cumulative average abnormal return (which we simply refer to as CAR) to its estimated standard error, and is given by

$$\sum_{t=-5}^{t=+5}\bar{A}_t \Bigg/ \sqrt{\sum_{t=-5}^{t=+5}\hat{S}^2(\bar{A}_t)} \sim N(0,1). \tag{7}$$

Table 2 presents the event study results for loan-bond pairs of the same company using the market-model adjusted method. We find evidence consistent with the default expectation hypothesis described in Section 3.1, namely that loans decline in price by a smaller amount as compared to bonds around default days. Specifically, loans fall by 19.51% during the 21 day [-10,+10] window surrounding loan default dates, while bonds fall by 47.40%. The difference in the loan average CAR (loan ACAR) and the bond average CAR (bond ACAR) of 27.89% (i.e., -19.51%-(-47.40%)) is statistically significant at the 1% level (Z-stat 4.51).[22] Similar results are found surrounding bond default dates as well. That is, loans fall by 20.00% during

[22]The Z statistic for the difference in ACARs is based on a paired difference test of CARs of matched loan-bond pairs.

the 21 day window surrounding bond default dates, as compared to the 33.73% fall for bonds. The difference in ACARs of 13.73% is statistically significant at the 10% level (Z-stat 1.72). Other event windows, namely 3 day [-1,+1] window, and 11 day [-5,+5] window surrounding loan default days and bond default dates produce similar results.[23] So, while firms typically show signs of operating and financial problems prior to default, there is significant price deterioration just prior to and just after the event date as evidenced in the larger event window, e.g., 21 day window.

For robustness purposes, we also examined the event study results using the remaining five measures: (a) unadjusted, (b) mean-adjusted, (c) market-adjusted, (d) Fama-French three-factor model, and (e) a loan-bond-stock three-factor model (i.e., where the three factors are the return on a loan index, the return on a bond index, and the return on a stock index) adjusted CARs. The results, tabulated in Appendix 2 are qualitatively similar to those in Table 2. Hence for the remainder of the paper, we present our event study results based on market-model adjusted CARs.

In summary (so far), we find support for the default expectation hypothesis. That is, the price reaction of loans is less adverse as compared to that of bonds around loan default dates and bond default dates. Our results are generally robust to the choice of event window (i.e., 3-day, 11-day or 21-day event window), as well as the choice of the method of computing abnormal returns (i.e., unadjusted, mean-adjusted, market-adjusted, market-model adjusted, Fama-French three-factor model-adjusted, or a loan-bond-stock three-factor model adjusted). However, the event study results have, so far, controlled only for the company name, and not for security specific characteristics, such as maturity, issue size, seniority, and collateral. We next turn our attention to these issues.

4.2.2. Multivariate results

For ease of interpretation of coefficients in the regression analysis, we stack the loan-bond pair observations, and define the dependent variable as simply the price decline, i.e.,

[23] The only exception is that the difference in ACARs for the 3 day window around bond default dates has the predicted sign but is not statistically significant.

the negative cumulative abnormal return (NCAR), where NCAR=-CAR. For example, if the CAR is -19.51% for a loan and -47.40% for a bond in a loan-bond pair, the dependent variable NCAR takes a value of 19.51% for a loan observation, and 47.40% for a bond observation in our regressions. Thus, a single loan-bond pair contributes to two observations in a stacked regression. We focus on market-model adjusted NCAR during the 21-day event window, i.e., [-10,+10]. To measure the priority structure of loans and bonds, we incorporate the seniority and collateral information of a loan or a bond, using the classification of Altman and Kishore (1996). We classify the loans and bonds into four different categories (see Appendix 1 for details) based on security-specific information from the Loan Pricing Corporation (LPC) for loans, and the description of a bond in the bond default dataset, i.e., (a) Senior secured, (b) Senior unsecured, (c) Senior subordinated, and (d) Subordinated and others.[24] We categorize these descriptive variables into three separate dummy variables corresponding to: Senior secured, Senior unsecured, and Senior subordinated types.[25] The independent variables used in some or all of the OLS regressions are:

LOAN DUMMY: An indicator variable that takes a value of one for a loan, and zero otherwise.

LOAN DEFAULT DUMMY: An indicator variable that takes a value of one if it is a loan default, and zero otherwise.

LN(MATURITY): Stands for natural log of one plus remaining maturity (in years) as on a default date.

LN(AMOUNT): Stands for natural log of one plus amount of the loan or bond issue (in $ millions).

SENIOR SECURED: An indicator variable that takes a value of one if a loan or a bond is senior secured, and zero otherwise.

SENIOR UNSECURED: An indicator variable that takes a value of one if a loan or a bond

[24] We combine others, such as discount and junior subordinated categories (since there were relatively few such loans and bonds) with the Subordinated into a single category.

[25] Since we include an intercept term in an OLS regression, we can only include three dummy variables (of the four) to avoid the problem of linear dependence of the independent variables. Consequently, we drop the dummy variable corresponding to "Subordinated and others".

is senior unsecured, and zero otherwise.

SENIOR SUBORDINATED: An indicator variable that takes a value of one if a loan or bond is senior subordinated, and zero otherwise.

LOAN DUMMY x LOAN DEFAULT LEADS: An interactive indicator variable that takes a value of one if it is a loan and if the loan default is not preceded by a bond default date of the same loan-bond pair, and zero otherwise.

4.2.2.1. Discussion of the variables

We test the default expectation hypothesis described in Section 3.1 by examining the predicted sign of the LOAN DUMMY coefficient. We expect the LOAN DUMMY coefficient to be negative and statistically significant, i.e., we expect a loan to have a smaller price decline around a default date than that of a bond of the same company after adjusting for the additional control variables described below.

We include the following variables as control variables: First, LOAN DEFAULT DUMMY, an indicator variable for the type of default, namely whether it is a loan default or a bond default. On one hand, as delegated monitors or "insiders", banks are expected to be better able to distinguish ex ante among good and bad borrowers relative to investors in the bond markets where monitoring tends to be diffuse and subject to free rider problems. Strictly interpreted, this implies that loan defaults should be rare events. Consequently, a loan default, when it does occur, is likely to be more surprising than a bond default, and may reflect the potential loss of reputation of the bank (see Dahiya, Saunders, and Srinivasan (2003)). However, on the other hand, it can be argued that loan defaults are, by definition, less surprising than bond defaults due to bank monitoring. Whether the LOAN DEFAULT DUMMY will have a positive coefficient or a negative coefficient depends on which of these two effects dominate. Second, with respect to LN(MATURITY), we expect this variable to have a positive coefficient since longer-maturity debt issues are potentially subject to a greater interest-rate risk exposure, and can have a higher default risk (Flannery, 1986). In other words, we expect a larger price decline for longer-maturity issues.[26] Third, LN(AMOUNT). Larger issues, on one hand, are likely to be more liquid, associated with less uncertainty, and have more public information associated with them. However, on the other hand, larger issues may be more difficult to reorganize post-default. Whether the sign of the LN(AMOUNT) coefficient is positive or negative is an empirical question as to which of these two effects dominates. Fourth, the priority structure reflects the protection or safety cushion to a loan or bond holder in the event of default. For example, we expect the price decline for a SENIOR SECURED security to be the least, followed by that of a SENIOR UNSECURED security, which in turn is lower than that of a SENIOR SUBORDINATED security. Accordingly, we expect the coefficient of the SENIOR SECURED variable to be smaller than that of the SENIOR UNSECURED variable, which in turn should be smaller than that of the SENIOR SUBORDINATED variable. Finally, LOAN DUMMY x LOAN DEFAULT LEADS, an interactive indicator variable that reflects the timing of a default date and additionally serves as the first signal of financial distress.[27] As a result, the measured effect of the LOAN DUMMY is expected to be amplified when a loan default is not preceded by a bond default, i.e., we expect the interactive indicator variable to have a negative sign similar to the LOAN DUMMY coefficient.

4.2.2.2. Regression results

The multivariate regression results are presented in Tables 3-5. Table 3 presents the regression results on loan default dates only. Table 4 presents the regression results on bond default days only. Table 5 presents the results for loan and bond default days. The details

[26] It may be argued that conditional on default, a longer-maturity debt issue is less risky (than a shorter-term debt issue) since it provides a longer period of time for a firm to revert to normalcy in terms of its cash flows. However, such an argument crucially misses incorporating the fact that the shorter-term debt of the same borrower (including any new debt issued as part of a potential reorganization) enjoys time-seniority over the longer-term debt, making the longer-term debt issue potentially more risky (and hence should be associated with a larger price decline at default).

[27] Of the 74 loan-bond pairs in Table 2, 43 cases are when the loan default leads, 5 cases are when the bond default leads, and the remaining 26 loan-bond pairs comprise simultaneous loan-bond defaults, i.e., loan and bond defaults within two days of each other. Since there are relatively few instances (five) where a bond default leads, we did not include an additional interactive indicator variable due to concerns of multicollinearity.

of these regressions are discussed below.

Specifically in Table 3, we test five different specifications. We start with Model 1 where we regress NCAR on LOAN DUMMY. The coefficient on the LOAN DUMMY is negative and statistically significant, suggesting that the price decline is 27.89% lower for loans as compared to bonds.[28] Next, we augment Model 1 with LN(MATURITY) and LN(AMOUNT) as additional control variables to run the regression Model 2. The LOAN DUMMY continues to be negative and statistically significant. Next, we augment Model 1 with the indicator variables for the priority structure, namely SENIOR SECURED, SENIOR UNSECURED, and SENIOR SUBORDINATED to run the regression Model 3. The LOAN DUMMY continues to be negative and statistically significant and the coefficients on the priority structure variables have the correct sign and the correct relative magnitudes.[29] We next augment Model 3 with LN(MATURITY) and LN(AMOUNT) to run the regression Model 4. The LOAN DUMMY continues to be negative and statistically significant. Finally, we augment Model 4 with the LOAN DUMMY x LOAN DEFAULT LEADS indicator variable to run the regression Model 5. Interestingly, both the LOAN DUMMY and LOAN DUMMY x LOAN DEFAULT LEADS variables are each negative and statistically significant.

Table 4 presents the regression results around bond default dates only. The LOAN DUMMY is negative in all five specifications, and statistically significant in the last three cases (Models 3-5). The LOAN DUMMY x LOAN DEFAULT LEADS has the expected sign but is statistically insignificant around bond default days.

Finally, Table 5 combines the loan-bond pairs around loan default dates with the loan-bond pairs around bond default dates. By combining, we augment each of the five regression specifications in Tables 3 and 4 with a LOAN DEFAULT DUMMY variable. The LOAN DUMMY is negative and statistically significant in all five specifications which implies that a loan has a smaller price decline around a default date than that of a bond of the same company after controlling for other variables included in a regression specification.

[28]This is exactly the difference in loan and bond ACARs from Table 2, i.e., -19.51 - (-47.40) = 27.89%.

[29]It may be noted that the coefficients of SENIOR SECURED, SENIOR UNSECURED, and SENIOR SUBORDINATED variables which are measured relative to "Subordinated and Others" can take values up to -200% since the dependent variable, NCAR has a potential range of 200% (from -100% to +100%).

Overall, based on the regression results, we find evidence consistent with the default expectation hypothesis described in Section 3. That is, we find that the price reaction of loans is less adverse than that of bonds around both loan and bond default dates − our results are robust to controlling for security-specific characteristics, such as maturity, issue size, seniority, and collateral. Additionally, the price decline is significantly lower for loans as compared to bonds around loan default dates that are not preceded by a bond default date. We next test whether our results are robust to alternative explanations, such as recovery rates, liquidity, covenants, timing of defaults, and lender forbearance.

4.3. Alternative explanations

In this section we test for several alternative explanations of our results in Section 4.2. For the sake of brevity, we present evidence on whether differences in recovery rates, liquidity and covenants between loans and bonds fully explain the price declines around loan default dates.[30] In addition, we also examine whether timing differences between loan and bond defaults, or lender forbearance can explain away the difference in price decline of loans versus bonds.

4.3.1. Recovery rates

If we take as given that loans recover more than bonds post-default (See Appendix 3 for a historical tabulation of recovery rates by debt type and seniority from 1988-2Q 2003), this may explain relative loan and bond price declines around a default date. In other words, a loan price decline is smaller than a bond price decline around a default date simply because loans recover more than bonds. However, a stronger test is to see if loan price declines are less than bond price declines even after controlling for recoveries. We test for this by examining whether adding the recovery rates (as proxied by the price of the loan or the bond on the default date) to the final regression specification around loan default dates in Table

[30] The results are qualitatively similar for combined loan-bond pairs around default days (Table 5) and for loan-bond pairs around bond default days (Table 4), albeit marginally less significant in the latter case.

3 (i.e., Model 5) changes the statistical significance of the LOAN DUMMY coefficient.[31]

The results are presented in Table 6 (see Model 1). We find that the LOAN DUMMY coefficient continues to be negative and statistically significant when we include the recovery rate variables. This suggests that the price declines are not fully explained by the recovery rates, and the monitoring advantage of loans over bonds is an important factor in determining price declines around default dates after controlling for recoveries.

4.3.2. Liquidity

To test whether differences in liquidity of loans versus bonds explain the relative loan and bond price declines around a default date, we use two proxies for liquidity: First, issue size, which we included in the multivariate regressions (see Section 4.2.2. for details). Second, we use a scaled frequency of price changes of a loan (or a bond) as an additional proxy for liquidity, namely the number of non-zero daily return observations as a fraction of the number of daily return observations during the estimation period [-244,-11], further scaled by the standard deviation of daily returns during the same period.[32]

The results are presented in Table 6 (see Model 2). We find that the LOAN DUMMY coefficient continues to be negative and statistically significant when we include proxies for liquidity, such as issue size, and scaled frequency of price changes.[33] This suggests that the loan-bond price declines are not fully explained by differences in loan-bond liquidity, and the monitoring advantage of loans over bonds is an important factor in determining price

[31] See Altman and Kishore (1996) and Altman (1993) for more details. Prices at or soon after default are used in many default studies and reports, e.g., Altman (annually), Moody's (annually), as well as in the settlement process in the credit default swap market (usually 30 days after default). An alternative measure for the recovery rate is the price at the end of the restructuring process, e.g., Chapter 11 emergence, discounted back to the default date (See Altman and Eberhart (1994)). We have not used this measure since many of the defaults in our study period have not been concluded and the data is not readily available even when completed.

[32] This scaling allows for a consistent measurement of liquidity across securities of differential risk, where risk is proxied by the standard deviation of daily returns. However, our results are not dependent on this scaling. That is, the results are qualitatively similar (not reported here) if we use the frequency of price changes instead of scaled frequency of price changes.

[33] It is interesting to note that the coefficient estimates of both the liquidity proxies indicate that the price decline around default dates is higher for loans and bonds that are more liquid relative to ones that are less liquid, perhaps due to the relative ease in selling a more liquid security around default news.

declines around default dates after controlling for liquidity differences of loans and bonds.

4.3.3. Covenants

To test whether differences in covenants of loans and bonds explain our results in Section 4.2.2, we construct a covenant score measure from a scale of 0 to 4 for each loan and bond in our sample, and include it as an additional explanatory variable in a multivariate regression. To construct this measure, we follow Smith and Warner (1979) to classify a covenant into one of four categories: First, investment covenants, such as restrictions on disposition of assets, and restrictions around a merger event in the future. Second, dividend covenants, such as restrictions on dividends and other distributions to equity holders. Third, financing covenants, such as restrictions on issuance of debt or equity in the future. Finally, payoff covenants, i.e., provisions that modify the payoffs to security holders, such as sinking funds, convertibility and callability provisions. The data sources we used for covenants is the Dealscan database for loans and the Fixed Income Securities Database for bonds. We consider both the explicit information (e.g., a restriction on issuance of future debt) and implicit information (e.g., a leverage covenant due to which a firm cannot exceed a certain leverage, implies a restriction on future debt financing) in classifying covenants into the four category types − both these covenants are classified as financing covenants. We next follow an approach similar to the one used by Bagnani et al (1994) of creating separate dummy variables for whether a loan or a bond has at least one covenant in a category type. Specifically, INVCOV = 1 for at least one investment covenant, DIVCOV = 1 for at least one dividend covenant, FINCOV = 1 for at least one financing covenant, and PAYCOV = 1 for at least one covenant modifying the payoff to investors. All dummy variables are zero otherwise. COVENANT SCORE is defined as the sum of these four dummy variables. Consequently, COVENANT SCORE can take the lowest value of zero for a loan or a bond that has no restrictive covenants in any of the four category types, and the highest value of four for a loan or a bond that has all the four category types.

The results are presented in Table 6 (see Model 3). We find that the LOAN DUMMY coefficient continues to be negative and statistically significant, and the coefficient of COVENANT SCORE is not statistically different from zero. This suggests that the loan-bond price declines are not fully explained by differences in loan-bond covenants, and the monitoring advantage of loans over bonds is an important factor in determining price declines around default dates.

4.3.4. Timing of defaults

To test whether our loan-bond price declines can be explained by the difference in timing of a loan default and a bond default of the same borrower, we included an indicator variable LOAN DUMMY x LOAN DEFAULT LEADS in the multivariate regression results in Section 4.2.2 (See, for example, Model 5 of Table 3).

The regression results are reproduced in Table 6 (see Model 4). We find that the loan dummy coefficient is negative and statistically significant, and that the loan-bond price declines are only partially explained by the differences in loan-bond default dates of the same borrower. Next, we augment this regression with the variables proxying for recovery rates, liquidity, and covenants. The regression results, presented in Table 6 (see Model 5) show that the LOAN DUMMY coefficient continues to be negative and statistically significant, suggesting that the monitoring advantage of loans over bonds is an important factor in determining price declines around default days, even after controlling for maturity, seniority, collateral, recoveries, liquidity and covenant characteristics.

As an additional robustness test, we focus our attention on the 26 loan-bond pairs with simultaneous loan-bond defaults. This subsample of 26 loan-bond pairs is not influenced by any timing differences between loan and bond default days, and hence can be used as an additional test of the monitoring role of loans over bonds. However given the small size of this sample, we need to be cautious in the interpretation of the results. The univariate results of the raw unadjusted returns (our first measure of cumulative abnormal returns) are shown in panel A of Table 7. We find evidence consistent with the default expectation hypothesis described in Section 3.1. That is, we find that the LOAN ACAR is significantly lower than the BOND ACAR for the [-5,+5] and [-10,+10] event windows. The results are qualitatively similar with the market-model adjusted CARs (see panel B of Table 7), albeit marginally weaker.

4.3.5. Lender forbearance

A loan may not be considered to be in default when a company misses a promised payment but rather only after a certain grace period following a minimized payment during which lenders may provide the borrower forbearance from making the promised payment. In contrast a bond is considered to be in default as soon as the company misses a promised payment (i.e., no grace period). This may bias the differential cumulative abnormal returns of loans versus bonds around default dates. In other words, the cumulative abnormal return of loans is smaller than that of bonds around default dates simply because the default dates may be biased due to bank forbearance on delinquent loans. We test for this alternative explanation by examining whether the cumulative abnormal return results change if we expand the event window to include a possible forbearance period of 30-90 days − loans that fail to accrue interest for more than 90 days are generally considered non-performing assets.[34]

The results are presented in Table 8 (corresponding to Table 2) for three different expanded event windows to capture a possible forbearance period of one month, two months or three months, i.e., for windows [-20,+10], [-40,+10] and [-60,+10], assuming each month corresponds to approximately 20 business days based on an estimation window of [-244,-61]. We find that the loan ACAR is smaller than bond ACAR in each of these cases where we allow for a potential forbearance period of respectively one month, two months, and three months.

4.4. Loans versus stocks

Previous empirical literature tests the monitoring role of loans by examining the stock

[34] The Federal Reserve usually treats a loan as non-performing if the borrower does not pay interest on the loan for more than 30 days.

price reaction of a borrower to the announcement of a new loan or a renewal of an existing loan to a borrower. Such tests may be viewed as indirect tests of the monitoring role of loans since direct tests would measure the price reaction of the loans rather than that of the stocks. In this section, we propose a direct test (due to the availability of secondary market loan price data) by examining the price reaction of loans as compared to that of stocks around loan default days and bond default days. Specifically, we examine whether our loan-bond results also extend to stocks, allowing us to make a similar assessment of the return performance of loans and stocks. This will also allow us to benchmark our loan-bond results.

Table 9 presents event study results for 29 loan-stock pairs around loan default dates and 59 stock-loan pairs around bond default days. This table includes matched loan-stock pairs where we are able to compute the CAR based on the market-model adjusted method for the [-10,+10] event window. That is, the return based on a market-model regression (using a market index such as the S&P/LSTA Leveraged Loan Index for loans, or a value-weighted NYSE/NASDAQ/AMEX index for stocks) is subtracted from the loan or stock daily return respectively.

We find evidence consistent with the default expectation hypothesis described in Section 3, namely that loan returns fall by a smaller amount as compared to stocks around default days. In particular, loans fell by 4.87% during the 11 day [-5,+5] window surrounding loan default dates, while stocks fell by 32.84%. The difference in the loan average CAR (loan ACAR) and the stock average CAR (stock ACAR) of 27.97% (i.e., -4.87%-(-32.84%)) is statistically significant at the 1% level (Z-stat 2.94). Similar results are found surrounding bond default dates as well. Specifically, loans fell by 4.30% during the 11 day window surrounding bond default dates, as compared to the 25.39% fall for stocks. The difference in ACARs of 21.09% is statistically significant at the 1% level (Z-stat 4.57). Other event windows, namely 3 day [-1,+1] window, and 21 day [-10,+10] windows produce similar results with the exception of the 21 day window around bond default dates (has the predicted sign but is not statistically significant).

5. Conclusions

This paper examines the informational efficiency of loans relative to bonds surrounding loan default dates and bond default dates using a unique dataset of daily secondary market prices during 11/1999-06/2002. We find that the return correlation between loans and bonds is relatively low for the entire sample period but is considerably higher during a 21-day event window surrounding a default date.

Consistent with a view that the surprise or unexpected component of a default is likely to be smaller for banks than for bond investors because banks are continuous monitors whereas monitoring in the bond market is more diffuse, we find that the price reaction of loans is less adverse than that of bonds around loan and bond default dates. Interestingly, where a loan default date is not preceded a bond default date of the same company, we find that the differential in the price reaction of loans versus bonds is higher around such a loan default date since it also acts as a first signal of distress. Overall, we find that the loan market is informationally more efficient than the bond market around default dates. Preliminary evidence also suggests that our results extend to stocks.

The results of our paper have important implications in terms of the impact of defaults on loans and bonds, the monitoring of loans versus bonds, the benefits of loan monitoring for other financial markets (such as the bond market and the stock market), and on the benefits of including loans as an asset class in an investment portfolio along with bonds and stocks.

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TABLE 1
Average return correlations between loans and bonds around default dates (matched by borrower name)

This table presents the average correlation and the average t-statistic (of testing whether the correlation coefficient is significantly different from zero) between daily returns of loans and bonds of the same company around default dates. The return data for loans is from the Loan Syndications and Trading Association (LSTA) and the return data for bonds is from the *Salomon* Yield Book. The average correlations are presented for the overall sample period and for several segments of time periods: (a) Pre-estimation period: on or preceding day -245, (b) Estimation period: [-244,-11], which is further broken down into sub periods as shown below, (c) Event window: [-10,+10], and (d) Post-event period: on or following day +11, where day 0 refers to the loan default date in Panel A, and to the bond default date in Panel B. The superscripts a, b, and c stand for significance at the 1%, 5%, and 10% levels using a two-tailed test.

Panel A: Loan default dates

Time Period	Mean	T-statistic
Pre-estimation period [≤-245]	-0.00	-0.22
Estimation period [-244,-11]	0.12	1.97[b]
– Subsegment [-244,-121]	0.02	0.29
– Subsegment [-61,-120]	0.02	0.10
– Subsegment [-31,-60]	0.03	0.14
– Subsegment [-11,-30]	0.26	1.34
Event window [-10,+10]	0.43	2.64[a]
Post-event period [≥ +11]	0.02	0.34

Panel B: Bond default dates

Time Period	Mean	T-statistic
Pre-estimation period [≤-245]	0.01	0.01
Estimation period [-244,-11]	0.01	0.13
– Subsegment [-244,-121]	0.01	0.19
– Subsegment [-61,-120]	-0.02	-0.25
– Subsegment [-31,-60]	0.03	0.24
– Subsegment [-11,-30]	-0.00	-0.00
Event window [-10,+10]	0.15	0.93
Post-event period [≥ +11]	0.04	0.44

TABLE 2
Average cumulative abnormal returns of matched loan-bond pairs around default dates (matched by borrower name)

This table presents the average cumulative abnormal return (ACAR) of matched loan-bond pairs (based on the name of the borrower) surrounding a default date (day 0), namely a loan default date or a bond default date of the same company. This table includes matched loan-bond pairs where we are able to compute the CAR based on the market-model adjusted method for the [-10,+10] event window. That is, the return based on a market-model regression using a market index (such as the S&P/LSTA Leveraged Loan Index for loans, or the Lehman Brothers U.S. Corporate Intermediate Bond Index for bonds) is subtracted from the loan or bond daily return respectively. The Z statistics of ACARs (shown in parentheses) are computed using the methodology of Brown and Warner (1985) that considers both the time-series and cross-sectional dependence in returns. The Z statistics for the difference in ACARs are based on a paired difference test of CARs of matched loan-bond pairs, and are shown in parentheses, where a, b, and c stand for significance at the 1%, 5%, and 10% levels using a two-tailed test.

Panel A: Loan default dates

Event window	Loan ACAR (%) (1)	Bond ACAR (%) (2)	Difference in ACAR (%) (3) = (1) - (2)
[-1,+1]	-4.06	-20.92	16.86
	(-4.48)[a]	(-9.13)[a]	(7.71)[a]
[-5,+5]	-9.82	-38.16	28.34
	(-5.67)[a]	(-8.69)[a]	(6.56)[a]
[-10,+10]	-19.51	-47.40	27.89
	(-8.15)[a]	(-7.82)[a]	(4.51)[a]
Obs	74	74	

Panel B: Bond default dates

Event window	Loan ACAR (%) (4)	Bond ACAR (%) (5)	Difference in ACAR (%) (6) = (4) - (5)
[-1,+1]	-3.37	-5.43	2.06
	(-3.51)[a]	(-2.09)[b]	(0.83)
[-5,+5]	-12.98	-28.84	15.86
	(-7.07)[a]	(-5.81)[a]	(2.99)[a]
[-10,+10]	-20.00	-33.73	13.73
	(-7.88)[a]	(-4.92)[a]	(1.72)[c]
Obs	69	69	

TABLE 3
Linear regression of negative cumulative abnormal return around loan default dates

This table presents OLS estimates of regression specifications determining the cumulative abnormal return (CAR) performance of loans and bonds surrounding loan default dates. This table includes loans, and bonds where we are able to compute the CAR based on the market-model adjusted method for the [-10,+10] event window. The dependent variable NEGATIVE CUMULATIVE ABNORMAL RETURN, NCAR[-10,+10] equals -CAR[-10,+10], where day [0] refers to a default date, namely the loan default date or the bond default date of the same company. The CARs are computed based on market-model adjustment, i.e., the return based on a market-model regression (using a market index such as the S&P/LSTA Leveraged Loan Index for loans and the Lehman Brothers U.S. Corporate Intermediate Bond Index for bonds) is subtracted from the loan or bond daily return. The independent variables are as follows: LOAN DUMMY takes a value of one if it is a loan, and zero otherwise. LN(MATURITY) stands for natural log of one plus remaining maturity (in years) as on a default date. LN(AMOUNT) stands for natural log of one plus amount of the loan or bond issue (in $ millions). SENIOR SECURED, SENIOR UNSECURED, and SENIOR SUBORDINATED each take a value of one if a loan or bond is classified like-wise and zero otherwise. LOAN DUMMY x LOAN DEFAULT LEADS is an interactive dummy variable that takes a value of one if it is a loan and if the loan default date is not preceded by a bond default date for the same loan-bond pair, and zero otherwise. The t ratios shown in parentheses are adjusted for heteroskedasticity using White's (1980) variance-covariance matrix (a, b, and c stand for significance at the 1%, 5%, and 10% levels using a two-tailed test).

Dependent Variable: -CAR[-10,+10], Market-model adjusted (%)

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
INTERCEPT	47.40	12.81	88.46	-14.23	-6.98
	(6.65)^a	(0.48)	(6.26)^a	(-0.58)	(-0.26)
LOAN DUMMY	-27.89	-17.28	-41.54	-34.53	-19.01
	(-3.71)^a	(-2.88)^a	(−4.95)^a	(-5.26)^a	(-2.35)^b
LN(MATURITY)		30.88		29.98	26.36
		(3.83)^a		(4.95)^a	(4.21)^a
LN(AMOUNT)		-3.54		7.69	8.52
		(-0.68)		(2.18)^b	(2.38)^b
SENIOR SECURED			-100.58	-105.99	-111.62
			(-6.33)^a	(-7.55)^a	(-7.97)^a
SENIOR UNSECURED			-38.60	-22.33	-23.22
			(-4.22)^a	(-2.76)^a	(-2.82)^a
SENIOR SUBORDINATED			-22.27	-16.86	-24.16
			(-1.71)^c	(-1.56)	(-2.06)^b
LOAN DUMMY x LOAN DEFAULT LEADS					-24.46
					(-3.25)^a
Observations	148	148	148	148	148
Adjusted R^2	0.08	0.14	0.38	0.46	0.47

TABLE 4
Linear regression of negative cumulative abnormal return around bond default dates

This table presents OLS estimates of regression specifications determining the cumulative abnormal return (CAR) performance of loans and bonds surrounding loan default dates. This table includes loans, and bonds where we are able to compute the CAR based on the market-model adjusted method for the [-10,+10] event window. The dependent variable NEGATIVE CUMULATIVE ABNORMAL RETURN, NCAR[-10,+10] equals -CAR[-10,+10], where day [0] refers to a default date, namely the loan default date or the bond default date of the same company. The CARs are computed based on market-model adjustment, i.e., the return based on a market-model regression (using a market index such as the S&P/LSTA Leveraged Loan Index for loans and the Lehman Brothers U.S. Corporate Intermediate Bond Index for bonds) is subtracted from the loan or bond daily return. The independent variables are as follows: LOAN DUMMY takes a value of one if it is a loan, and zero otherwise. LN(MATURITY) stands for natural log of one plus remaining maturity (in years) as on a default date. LN(AMOUNT) stands for natural log of one plus amount of the loan or bond issue (in $ millions). SENIOR SECURED, SENIOR UNSECURED, and SENIOR SUBORDINATED each take a value of one if a loan or bond is classified like-wise and zero otherwise. LOAN DUMMY x LOAN DEFAULT LEADS is an interactive dummy variable that takes a value of one if it is a loan and if the loan default date is not preceded by a bond default date for the same loan-bond pair, and zero otherwise. The t ratios shown in parentheses are adjusted for heteroskedasticity using White's (1980) variance-covariance matrix (a, b, and c stand for significance at the 1%, 5%, and 10% levels using a two-tailed test).

Dependent Variable: -CAR[-10,+10], Market-model adjusted (%)

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
INTERCEPT	33.73	-67.71	78.10	-45.35	-40.71
	$(3.61)^a$	$(-1.89)^c$	$(5.11)^a$	(-1.16)	(-1.01)
LOAN DUMMY	-13.73	-6.38	-34.47	-27.27	-23.05
	(-1.38)	(-0.69)	$(-2.85)^a$	$(-2.33)^b$	$(-1.74)^c$
LN(MATURITY)		14.39		16.44	18.06
		(1.49)		$(1.70)^c$	$(1.74)^c$
LN(AMOUNT)		12.19		14.52	13.64
		$(2.70)^a$		$(2.73)^a$	$(2.44)^b$
SENIOR SECURED			-91.06	-93.64	-95.81
			$(-5.38)^a$	$(-5.44)^a$	$(-5.40)^a$
SENIOR UNSECURED			-47.90	-32.69	-35.78
			$(-4.13)^a$	$(-2.55)^b$	$(-2.45)^b$
SENIOR SUBORDINATED			-31.99	-25.44	-29.45
			$(-2.72)^a$	$(-1.66)^c$	$(-1.66)^c$
LOAN DUMMY x LOAN DEFAULT LEADS					-10.39
					(-1.24)
Observations	138	138	138	138	138
Adjusted R^2	0.01	0.02	0.16	0.19	0.19

TABLE 5
Linear regression of negative cumulative abnormal returns around default dates

This table presents OLS estimates of regression specifications determining the cumulative abnormal return (CAR) performance of loans and bonds surrounding default dates. This table includes loans, and bonds where we are able to compute the CAR based on the market-model adjusted method for the [-10,+10] event window. The dependent variable NEGATIVE CUMULATIVE ABNORMAL RETURN, NCAR[-10,+10] equals -CAR[-10,+10], where day [0] refers to a default date, namely the loan default date or the bond default date of the same company. The CARs are computed based on market-model adjustment, i.e., the return based on a market-model regression (using a market index such as the S&P/LSTA Leveraged Loan Index for loans and the Lehman Brothers U.S. Corporate Intermediate Bond Index for bonds) is subtracted from the loan or bond daily return. The independent variables are as follows: LOAN DEFAULT DUMMY takes a value of one if it is a loan default, and zero otherwise. LOAN DUMMY takes a value of one if it is a loan, and zero otherwise. LN(MATURITY) stands for natural log of one plus remaining maturity (in years) as on a default date. LN(AMOUNT) stands for natural log of one plus amount of the loan or bond issue (in $ millions). SENIOR SECURED, SENIOR UNSECURED, and SENIOR SUBORDINATED each take a value of one if a loan or bond is classified like-wise and zero otherwise. LOAN DUMMY x LOAN DEFAULT LEADS is an interactive dummy variable that takes a value of one if it is a loan and if the loan default date is not preceded by a bond default date for the same loan-bond pair, and zero otherwise. The t ratios shown in parentheses are adjusted for heteroskedasticity using White's (1980) variance-covariance matrix (a, b, and c stand for significance at the 1%, 5%, and 10% levels using a two-tailed test).

Dependent Variable: -CAR[-10,+10], Market-model adjusted (%)

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
INTERCEPT	37.39	-48.02	78.01	-43.38	-36.18
	$(5.15)^a$	$(-2.31)^b$	$(7.08)^a$	$(-1.85)^c$	(-1.48)
LOAN DEFAULT DUMMY	6.60	11.80	12.39	15.77	19.09
	(1.06)	$(1.85)^c$	$(2.12)^b$	$(2.80)^a$	$(3.16)^a$
LOAN DUMMY	-21.06	-11.17	-38.18	-30.92	-22.22
	$(-3.40)^a$	$(-2.13)^b$	$(-5.46)^a$	$(-5.19)^a$	$(-2.97)^a$
LN(MATURITY)		19.48		20.38	20.65
		$(3.30)^a$		$(4.26)^a$	$(4.53)^a$
LN(AMOUNT)		7.67		13.13	12.19
		$(2.39)^b$		$(4.10)^a$	$(3.65)^a$
SENIOR SECURED			-96.74	-101.75	-105.03
			$(-8.42)^a$	$(-8.91)^a$	$(-9.20)^a$
SENIOR UNSECURED			-43.99	-29.41	-30.06
			$(-6.37)^a$	$(-3.98)^a$	$(-4.01)^a$
SENIOR SUBORDINATED			-27.78	-22.60	-28.15
			$(-3.16)^a$	$(-2.45)^b$	$(-2.80)^a$
LOAN DUMMY x					
LOAN DEFAULT LEADS					-17.07
					$(-3.13)^a$
Observations	286	286	286	286	286
Adjusted R^2	0.04	0.07	0.26	0.31	0.31

TABLE 6
Robustness tests for alternative explanations of price declines around loan default dates

This table presents robustness tests for alternative explanations of price declines around loan default dates. See TABLE 4 Model 5 for the regression specification and definitions of variables. Additional variables used in this table are: RECOVERY RATE refers to the amount an investor expects from her investment in the loan or the bond subsequent to the default date, and is proxied by the price of the loan or the bond on the loan default date. SCALED FREQUENCY OF PRICE CHANGES refers to the number of non-zero daily return observations as a fraction of the number of daily return observations during the estimation period [-244,-11], further scaled by the standard deviation of daily returns during the same period. COVENANT SCORE is the sum of four dummy variables that represent four loan/bond covenants as described in Smith and Warner (1979), namely, INVCOV = 1 for restrictions on investments, DIVCOV = 1 for restrictions on dividends, FINCOV = 1 for restrictions of financing, and PAYCOV = 1 for covenants modifying payoff to investors. The t ratios shown in parentheses are adjusted for heteroskedasticity using White's (1980) variance-covariance matrix (a, b, and c stand for significance at the 1%, 5%, and 10% levels using a two-tailed test).

Dependent Variable: -CAR[-10,+10], Market-model adjusted (%)

	Recovery rates	Liquidity differences	Covenant differences	Timing of defaults	All (Models 1-4)
Variable	Model 1	Model 2	Model 3	Model 4	Model 5
INTERCEPT	66.88	-13.58	-13.36	-6.98	60.46
	$(2.64)^a$	(-0.48)	(-0.51)	(-0.26)	$(2.71)^a$
LOAN DUMMY	-8.96	-24.03	-17.99	-19.01	-25.25
	$(-2.24)^b$	$(-2.52)^b$	$(-2.19)^b$	$(-2.35)^b$	$(-3.91)^a$
LN(MATURITY)	6.17	26.84	26.49	26.36	0.12
	$(1.79)^c$	$(4.29)^a$	$(4.19)^a$	$(4.21)^a$	(0.03)
LN(AMOUNT)	5.12	9.92	8.37	8.52	9.56
	(1.48)	$(2.48)^b$	$(2.29)^a$	$(2.38)^b$	$(2.59)^a$
SENIOR SECURED	-105.85	-115.38	-115.96	-111.62	-125.30
	$(-7.50)^a$	$(-7.87)^a$	$(-7.70)^a$	$(-7.97)^a$	$(-8.48)^a$
SENIOR UNSECURED	3.63	-32.63	-25.46	-23.22	-29.00
	(0.30)	$(-3.23)^a$	$(-2.90)^a$	$(-2.82)^a$	$(-2.31)^b$
SENIOR SUBORDINATED	-2.01	-27.09	-27.57	-24.16	-9.98
	(-0.16)	$(-2.31)^b$	$(-2.16)^b$	$(-2.06)^b$	(-0.92)
LOAN DUMMY x LOAN DEFAULT LEADS	-10.80	-24.81	-23.05	-24.46	-4.90
	(-1.43)	$(-3.19)^a$	$(-3.12)^a$	$(-3.25)^a$	(-0.66)
RECOVERY RATE	-1.04				-1.47
	$(-4.07)^a$				$(-5.24)^a$
SCALED FREQUENCY OF PRICE CHANGES		0.09			0.41
		$(2.04)^b$			$(4.30)^a$
COVENANT SCORE (0-4)			3.13		4.00
			(1.59)		$(2.38)^b$
Observations	148	148	148	148	148
Adjusted R^2	0.58	0.47	0.48	0.47	0.65

TABLE 7
Average cumulative abnormal returns of matched loan-bond pairs with the same loan and bond default days (matched by borrower name)

This table presents the average cumulative abnormal return (ACAR) of matched loan-bond pairs (based on the name of the borrower) with the same loan and bond default days (i.e., within 2 days of each other) surrounding a default date (day 0), namely a loan default date or a bond default date of the same company. Panel A includes matched loan-bond pairs where we are able to compute the unadjusted cumulative returns for the [-10,+10] event window. That is, the unadjusted loan or bond daily return respectively. Panel B includes matched loan-bond pairs where we are able to compute the CAR based on the market-model adjusted method for the [-10,+10] event window. That is, the return based on a market-model regression using a market index (such as the S&P/LSTA Leveraged Loan Index for loans, or the Lehman Brothers U.S. Corporate Intermediate Bond Index for bonds) is subtracted from the loan or bond daily return respectively. The Z statistics of ACARs (shown in parentheses) are computed using the methodology of Brown and Warner (1985) that considers both the time-series and cross-sectional dependence in returns. The Z statistics for the difference in ACARs are based on a paired difference test of CARs of matched loan-bond pairs, and are shown in parentheses, where a, b, and c stand for significance at the 1%, 5%, and 10% levels using a two-tailed test.

Panel A: Unadjusted returns

Event window	Loan ACAR (%) (1)	Bond ACAR (%) (2)	Difference in ACAR (%) (3) = (1) - (2)
[-1,+1]	-3.04	-2.56	-0.48
	(-1.28)	(-0.42)	(-0.17)
[-5,+5]	-20.51	-69.87	49.36
	$(-4.50)^a$	$(-6.03)^a$	$(4.32)^a$
[-10,+10]	-51.25	-82.90	31.65
	$(-8.15)^a$	$(-5.17)^a$	$(1.81)^c$
Obs	26	26	

Panel B: Market-model adjusted returns

Event window	Loan ACAR (%) (1)	Bond ACAR (%) (2)	Difference in ACAR (%) (3) = (1) - (2)
[-1,+1]	-0.01	-0.00	-0.01
	(-0.57)	(-0.06)	(-0.34)
[-5,+5]	-14.66	-60.66	46.00
	$(-3.30)^a$	$(-5.22)^a$	$(4.06)^a$
[-10,+10]	-41.89	-64.96	23.07
	$(-6.82)^a$	$(-4.04)^a$	(1.31)
Obs	26	26	

TABLE 8
Average cumulative abnormal returns of matched loan-bond pairs around default dates (matched by borrower name)

This table presents the average cumulative abnormal return (ACAR) of matched loan-bond pairs (based on the name of the borrower) surrounding a default date (day 0), namely a loan default date or a bond default date of the same company. This table includes matched loan-bond pairs where we are able to compute the CAR based on the market-model adjusted method for the [-60,+10] event window. That is, the return based on a market-model regression during [-244,-61] using a market index (such as the S&P/LSTA Leveraged Loan Index for loans, or the Lehman Brothers U.S. Corporate Intermediate Bond Index for bonds) is subtracted from the loan or bond daily return respectively. The Z statistics of ACARs (shown in parentheses) are computed using the methodology of Brown and Warner (1985) that considers both the time-series and cross-sectional dependence in returns. The Z statistics for the difference in ACARs are based on a paired difference test of CARs of matched loan-bond pairs, and are shown in parentheses, where a, b, and c stand for significance at the 1%, 5%, and 10% levels using a two-tailed test.

Panel A: Loan default dates

Event window	Loan ACAR (%) (1)	Bond ACAR (%) (2)	Difference in ACAR (%) (3) = (1) - (2)
[-20,+10]	-20.04	-63.55	43.51
	(-30.87)^a	(-17.66)^a	(7.30)^a
[-40,+10]	-26.30	-76.66	50.36
	(-31.60)^a	(-16.61)^a	(5.97)^a
[-60,+10]	-29.98	-85.50	55.52
	(-30.52)^a	(-15.70)^a	(5.50)^a
Obs	55	55	

Panel B: Bond default dates

Event window	Loan ACAR (%) (4)	Bond ACAR (%) (5)	Difference in ACAR (%) (6) = (4) - (5)
[-20,+10]	-17.90	-46.95	29.05
	(-18.37)^a	(-7.07)^a	(3.37)^a
[-40,+10]	-25.68	-65.56	39.88
	(-20.55)^a	(-7.70)^a	(3.62)^a
[-10,+10]	-30.92	-66.28	35.36
	(-20.97)^a	(-6.59)^a	(2.93)^a
Obs	49	49	

TABLE 9
Average cumulative abnormal returns of matched loan-stock pairs around default dates (matched by borrower name)

This table presents the average cumulative abnormal return (ACAR) of matched loan-stock pairs surrounding a default date (day 0), namely a loan default date or a bond default date of the same company. This table includes matched loan-stock pairs where we are able to compute the CAR based on the market-model adjusted method for the [-10,+10] event window. That is, the return based on a market-model regression (using a market index such as the S&P/LSTA Leveraged Loan Index for loans, or a value-weighted NYSE/NASDAQ/AMEX index for stocks) is subtracted from the loan or stock daily return respectively. The number of observations is shown for the estimation window [-10,+10]. The *t* ratios of ACARs are computed using the methodology of Brown and Warner (1985) that considers both the time-series and cross-sectional dependence in returns. The *t* ratios for differences are based on pair-wise difference in the ACARs of matched loan-stock pairs. The *t* ratios are shown in parentheses, where a, b, and c stand for significance at the 1%, 5%, and 10% levels using a two-tailed test.

Panel A: Loan default dates

Event window	Loan ACAR (%) (1)	Stock ACAR (%) (2)	Difference in ACAR (%) (3) = (1) - (2)
[-1,+1]	0.21	-30.77	30.98
	(0.17)	(-5.63)^a	(3.62)^a
[-5,+5]	-4.87	-32.84	27.97
	(-2.08)^a	(-3.14)^a	(2.94)^a
[-10,+10]	-13.16	-52.14	38.98
	(-4.93)^a	(-4.04)^a	(5.08)^a
Obs	29	29	

Panel B: Bond default dates

Event window	Loan ACAR (%) (4)	Stock ACAR (%) (5)	Difference in ACAR (%) (6) = (4) - (5)
[-1,+1]	-0.38	-17.27	16.89
	(-0.76)	(-5.40)^a	(3.87)^a
[-5,+5]	-4.30	-25.39	21.09
	(-4.48)^a	(-4.14)^a	(4.57)^a
[-10,+10]	-6.38	-44.57	38.19
	(-4.76)^a	(-5.28)^a	(1.47)
Obs	59	59	

Appendix 1
Datasets used in this study

This appendix outlines a brief overview of the datasets that we use in this study. We list the providers of this data, and how the data was processed into individual datasets used in this study.

Loan price dataset

The source for this data is the Loan Syndications and Trading Association (LSTA) and Loan Pricing Corporation (LPC) mark-to-market pricing service, an independent and objective pricing service to more than 100 institutions, managing almost 175 portfolios with over $200 billion in bank loan assets. This unique dataset consists of daily bid and ask price quotes aggregated across dealers. Each loan has a minimum of at least two dealer quotes and a maximum of over 30 dealers, including all top broker-dealers. At the time we received the dataset from LSTA, there were 33 dealers providing quotes to the LSTA/LPC mark-to-market pricing service. These price quotes are obtained on a daily basis by LSTA in the late afternoon from the dealers and the price quotes reflect the market events for the day. The data items in this database include a unique loan identification number (LIN), name of the issuer (Company), type of loan, e.g., term loan (facility), date of pricing (Pricing Date), average of bid quotes (Avg Bid), number of bid quotes (Bid Quotes), average of second and third highest bid quote (High Bid Avg), average of ask quotes (Avg Ask), number of ask quotes (Ask Quotes), average of second and third lowest ask quotes (Low Ask Avg), and a type of classification based on the number of quotes received, e.g., Class II if 3 or more bid quotes.

The daily data from 11/1999 thru 06/2002 in the form of individual excel spreadsheets were combined in SAS based on the unique loan identification number (LIN). We excluded loans with a missing LIN since there is no unique way of combining them, e.g., if a company has three loans, and the LIN is missing on two of them. We have 543,526 loan-day observations in our loan price data spanning 1,863 loans.

Bond price (Yield Book) dataset

We extracted daily bond prices for the companies for which we have loans in the loan price dataset in the following manner: First, we found all the available matching Yield Book IDs from the Fixed Income Securities Database (FISD), namely the 9-digit identifiers comprising a 6 digit issuer cusip plus a 3 digit issue cusip for the bonds pertaining to the companies in the loan price dataset. The matching was done manually to ensure that we do not miss any bonds due to errors, such as an abbreviated company name in one database and its full name in another database. Second, we extracted daily prices of the bonds from the Salomon Yield Book based on their 9-digit identifiers. We have a total of 371,797 bond-day observations spanning 816 bonds.

Bond price (Datastream) dataset

We extracted daily bond prices for a subset of loans in the loan price dataset with a loan default date or a bond default date (the primary focus of this study) in the following manner: First, we found all the available matching Datastream IDs, namely the 6 digit Datastream codes for the bonds pertaining to the companies in the loan price dataset. The matching was done manually to ensure that we do not miss any bonds due to errors, such as an abbreviated company name in one database and its full name in another database. We check both the current list of Datastream codes of live bonds and the list on the Datastream Extranet which contains the dead bonds. Second, we extracted daily prices of the bonds from Datastream based on their 6-digit identifiers. We have a total of 91,760 bond-day observations spanning 248 bonds.

Stock price dataset

We extracted daily stock prices and returns for the companies for which we have loans in the loan price dataset in the following manner: First, we found all the available matching permnos for the stocks pertaining to the companies in the loan price dataset. The matching was done manually to ensure that we do not miss any stocks due to errors, such as an abbreviated company name in one database and its full name in another database, extra characters in one database as compared to the other. If we could still not find a match, we checked on Hoovers Online, Mergent Online and finally on Google. If the company is a subsidiary of a larger company we used the parent companys permno. Second, we extracted daily prices and stocks from the 2002 CRSP stock files based on the permnos. We have a total of 21,510 stock-day observations spanning 75 stocks corresponding to a subset of loans in the loan price dataset with a loan default date or a bond default date (the primary focus of this study).

Loan defaults dataset

The loan defaults dataset consists of loan defaults from the institutional loans market. We received this data from Portfolio Management Data (PMD), a business unit of Standard & Poors (recently changed its name to "Standard & Poor's Leveraged Commentary & Data") which has been tracking loan defaults in the institutional loans market since 1995. During our sample period we had 90 loan defaults.

Bond defaults dataset

The source for our bond defaults dataset is the "New York University (NYU) Salomon Center's Altman Bond Default Database". It is a comprehensive dataset of domestic corporate bond default dates starting from 1974. During our sample period we had 765 bond defaults pertaining to 366 companies.

Loan characteristics dataset

The source for our loan characteristics dataset is the Loan Pricing Corporation. The key data items are: (a) Name of the borrower, (b) Facility type: information on seniority of a facility, and whether it is a term loan or revolver facility, (c) Facility amount, (d) Facility date, (e) Final maturity, (f) Security, e.g., Secured or Unsecured or what type of specific collateral (All assets, or Capital Stock of Operating Units etc.), (g) Loan Identification Number. We first matched the details of the loan from the loan price dataset, e.g., LIN, name of the borrower, and we created variables that denote the priority structure of a loan, e.g., SENIOR SECURED, SENIOR UNSECURED, and SENIOR SUBORDINATED (see Section 4.2.2.) based on Facility type and Security information.

Bond characteristics dataset

The source for our bond defaults dataset is the "New York University (NYU) Salomon Center's Altman Bond Default Database". To measure the priority structure of bonds, we incorporate the seniority and collateral information of a bond, using the classification of Altman and Kishore (1996). We classify bonds into four different categories based on the description of a bond in the bond defaults dataset: (a) Senior secured, (b) Senior unsecured, (c) Senior subordinated, and (d) Subordinated and others.

Indices dataset

The sources for the indices dataset is the S&P/LSTA Leveraged Loan Index from the Standard & Poor's, the Lehman Brothers U.S. Corporate Intermediate Bond Index from the Datastream, and the NYSE/AMEX/NASDAQ Value-weighted Index from the Center for Research in Securities Prices (CRSP) for the loan, bond and stock index returns. While the Lehman Brothers U.S. Corporate Intermediate Bond Index and the NYSE/AMEX/NASDAQ Value-weighted Index are both daily series, the S&P/LSTA Leveraged Loan Index is a weekly series during our sample period. We converted the S&P/LSTA Leveraged Loan Index weekly series to a daily series through linear intrapolation wherever necessary.

Appendix 2
Average cumulative abnormal returns of matched loan-bond pairs (matched by borrower name)

This table presents the average cumulative abnormal return (ACAR) of matched loan-bond pairs (based on the name of the borrower) surrounding a default date (day 0), namely a loan default date or a bond default date of the same company. This table includes matched loan-bond pairs where we are able to compute the CAR for the [-10,+10] event window. Panel A is based on unadjusted returns, Panel B is based on mean-adjusted returns, Panel C is based on market-adjusted returns, Panel D is based on a three-factor model (with the three factors between a loan index return, a bond index return, and a stock index return), and Panel E is based on the Fama-French three-factor model (see Section 4.2.1 for details). The Z statistics of ACARs (shown in parentheses) are computed using the methodology of Brown and Warner (1985) that considers both the time-series and cross-sectional dependence in returns. The Z statistics for the difference in ACARs are based on a paired difference test of CARs of matched loan-bond pairs, and are shown in parentheses, where a, b, and c stand for significance at the 1%, 5%, and 10% levels using a two-tailed test.

Panel A1: Unadjusted ACARs surrounding loan default dates

Event window	Loan ACAR (%) (1)	Bond ACAR (%) (2)	Difference in ACAR (%) (3) = (1) - (2)
[-1,+1]	-4.86	-21.94	17.08
	(-5.32)[a]	(-9.51)[a]	(7.90)[a]
[-5,+5]	-12.61	-42.25	29.64
	(-7.21)[a]	(-9.56)[a]	(6.73)[a]
[-10,+10]	-23.92	-55.38	31.46
	(-9.91)[a]	(-9.07)[a]	(5.14)[a]
Obs	74	74	

Panel A2: Unadjusted ACARs surrounding bond default dates

Event window	Loan ACAR (%) (4)	Bond ACAR (%) (5)	Difference in ACAR (%) (6) = (4) - (5)
[-1,+1]	-4.29	-7.05	2.76
	(-4.31)[a]	(-2.72)[a]	(1.09)
[-5,+5]	-16.23	-35.18	18.95
	(-8.52)[a]	(-7.10)[a]	(3.55)[a]
[-10,+10]	-25.55	-45.96	20.41
	(-9.71)[a]	(-6.71)[a]	(2.58)[a]
Obs	69	69	

Panel B1: Mean-adjusted ACARs surrounding loan default dates

Event window	Loan ACAR (%) (1)	Bond ACAR (%) (2)	Difference in ACAR (%) (3) = (1) - (2)
[-1,+1]	-4.54	-20.83	16.29
	(-4.99)[a]	(-9.06)[a]	(7.28)[a]
[-5,+5]	-11.44	-38.18	26.74
	(-6.56)[a]	(-8.67)[a]	(6.14)[a]
[-10,+10]	-21.70	-47.62	25.92
	(-9.00)[a]	(-7.83)[a]	(4.01)[a]
Obs	74	74	

Panel B2: Mean-adjusted ACARs surrounding bond default dates

Event window	Loan ACAR (%) (4)	Bond ACAR (%) (5)	Difference in ACAR (%) (6) = (4) - (5)
[-1,+1]	-3.88	-5.32	1.44
	(-3.91)[a]	(-2.06)[b]	(0.58)
[-5,+5]	-14.72	-28.83	14.11
	(-7.75)[a]	(-5.82)[a]	(2.67)[a]
[-10,+10]	-22.67	-33.83	11.16
	(-8.64)[a]	(-4.94)[a]	(1.37)
Obs	69	69	

Panel C1: Market-adjusted ACARs surrounding loan default dates

Event window	Loan ACAR (%) (1)	Bond ACAR (%) (2)	Difference in ACAR (%) (3) = (1) - (2)
[-1,+1]	-4.76	-22.21	17.45
	(-5.19)[a]	(-9.42)[a]	(8.14)[a]
[-5,+5]	-12.26	-42.79	30.53
	(-7.00)[a]	(-9.48)[a]	(6.88)[a]
[-10,+10]	-23.78	-56.34	32.56
	(-9.82)[a]	(-9.03)[a]	(5.28)[a]
Obs	74	74	

Panel C2: Market-adjusted ACARs surrounding bond default dates

Event window	Loan ACAR (%) (4)	Bond ACAR (%) (5)	Difference in ACAR (%) (6) = (4) - (5)
[-1,+1]	-4.29	-7.37	3.08
	(-4.34)[a]	(-2.84)[a]	(1.21)
[-5,+5]	-16.24	-36.11	19.87
	(-8.57)[a]	(-7.27)[a]	(3.72)[a]
[-10,+10]	-25.63	-47.31	21.68
	(-9.79)[a]	(-6.89)[a]	(2.72)[a]
Obs	69	69	

Panel D1: Three-factor model ACARs surrounding loan default dates

Event window	Loan ACAR (%) (1)	Bond ACAR (%) (2)	Difference in ACAR (%) (3) = (1) - (2)
[-1,+1]	-4.18	-21.52	17.34
	(-4.80)[a]	(-9.39)[a]	(8.13)[a]
[-5,+5]	-9.10	-38.62	29.52
	(-5.46)[a]	(-8.80)[a]	(6.57)[a]
[-10,+10]	-18.24	-47.50	29.26
	(-7.92)[a]	(-7.83)[a]	(4.53)[a]
Obs	74	74	

Panel D2: Three-factor model ACARs surrounding bond default dates

Event window	Loan ACAR (%) (4)	Bond ACAR (%) (5)	Difference in ACAR (%) (6) = (4) - (5)
[-1,+1]	-3.49	-5.58	2.09
	(-3.73)[a]	(-2.17)[b]	(0.83)
[-5,+5]	-12.19	-29.05	16.86
	(-6.80)[a]	(-5.91)[a]	(2.99)[a]
[-10,+10]	-18.61	-34.07	15.46
	(-7.51)[a]	(-5.02)[a]	(1.79)[c]
Obs	69	69	

Panel E1: Fama-French three-factor model ACARs surrounding loan default dates

Event window	Loan ACAR (%) (1)	Bond ACAR (%) (2)	Difference in ACAR (%) (3) = (1) - (2)
[-1,+1]	-4.57	-21.09	16.52
	(-4.99)[a]	(-9.14)[a]	(7.56)[a]
[-5,+5]	-11.42	-38.39	26.97
	(-6.51)[a]	(-8.69)[a]	(5.99)[a]
[-10,+10]	-21.58	-47.16	25.58
	(-8.91)[a]	(-7.73)[a]	(3.90)[a]
Obs	74	74	

Panel E2: Fama-French three-factor model ACARs surrounding bond default dates

Event window	Loan ACAR (%) (4)	Bond ACAR (%) (5)	Difference in ACAR (%) (6) = (4) - (5)
[-1,+1]	-3.98	-5.74	1.76
	(-4.04)[a]	(-2.21)[b]	(0.70)
[-5,+5]	-14.64	-28.09	13.45
	(-7.75)[a]	(-5.65)[a]	(2.54)[b]
[-10,+10]	-22.46	-34.11	11.65
	(-8.61)[a]	(-4.97)[a]	(1.41)
Obs	69	69	

Appendix 3
Recovery rates by debt type and seniority

This table summarizes three measures of recovery rates, namely trading prices just after default, and 30 days after default, and at ultimate recovery for the 1988-2Q 2003. The sources are: Altman-NYU Salomon Center Default database, prices from numerous broker dealers in distressed debt. Bank Loan data from 1996-2002 (for the first two measures), and Standard & Poor's LossStatsTM database from 1988-2Q-2003 for the third measure (ultimate recoveries discounted at each instrument's pre-default interest rate). Note that the Sub. Discounted Bonds category includes zero coupon and discounted bonds of all seniorities.

Debt Type/Seniority	Price at Default		Price 30 Days After Default		Ultimate recovery			
						Nominal	Discounted	Annual
	#obs.	Mean %	#obs.	Mean %	#obs.	Mean %	Mean %	IRR %
Bank Loans	262	69.2	750	58.0	750	88.9	78.8	20.0
Senior Secured Bonds	152	51.6	222	48.8	222	76.5	65.1	20.5
Senior Unsecured Bonds	752	32.4	419	30.3	419	54.9	46.4	23.0
Senior Subordinated Bonds	346	28.8	350	28.4	350	38.2	31.6	7.7
Subordinated Bonds	180	29.0	293	28.9	343	36.3	29.4	8.9
Sub. Discounted Bonds	130	20.4	–	–	43	–	22.0	–

Figure 1
Secondary Market for Loans